

Breakout session 1: The value of large ensembles for model evaluation, attribution and unraveling projection uncertainty

Isla Simpson
+workshop organizing committee



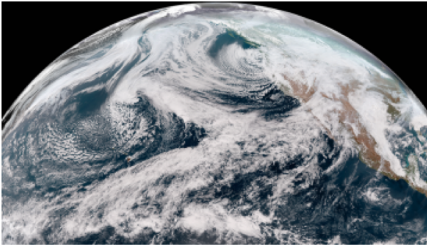
July, 2019



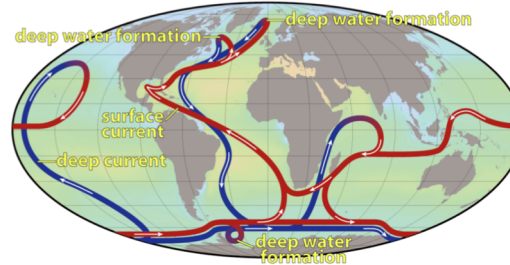
The purpose...

The purpose...

We have representation here from many different sub-fields within Earth Science



atmospheric scientists



oceanographers



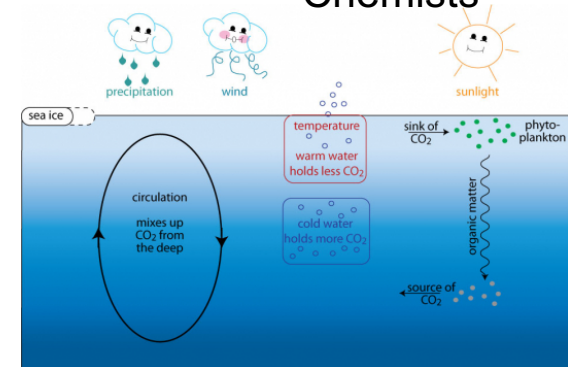
Chemists



Impacts experts



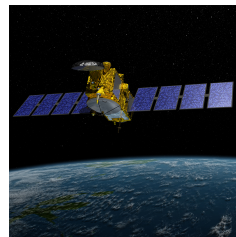
Ecologists



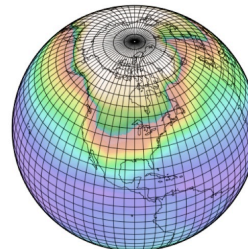
Ocean biogeochemists



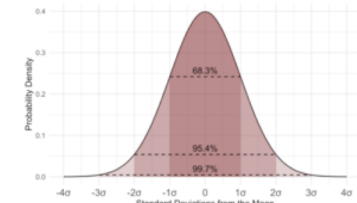
hydrologists



observationalists



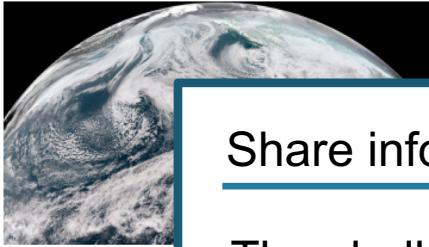
modelers



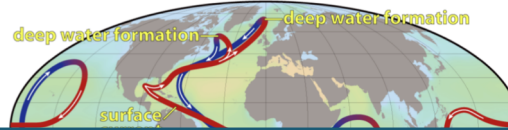
statisticians

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atmosph

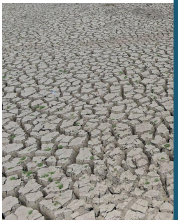


Share information and discuss across sub-fields...

The challenges we face with regards to identifying anthropogenic influences within the observational record

The approaches used to validate our models

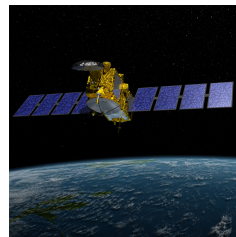
The largest contributors to projection uncertainties and how we go about reducing such uncertainties.



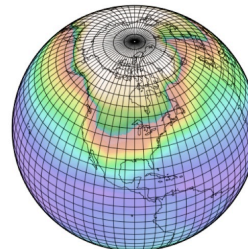
Impact



hydrologists

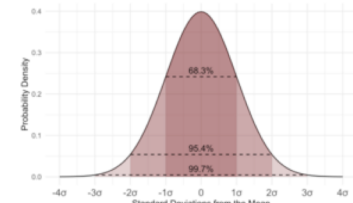


observationalists



modelers

Ocean biogeochemists



statisticians

Discussion questions...

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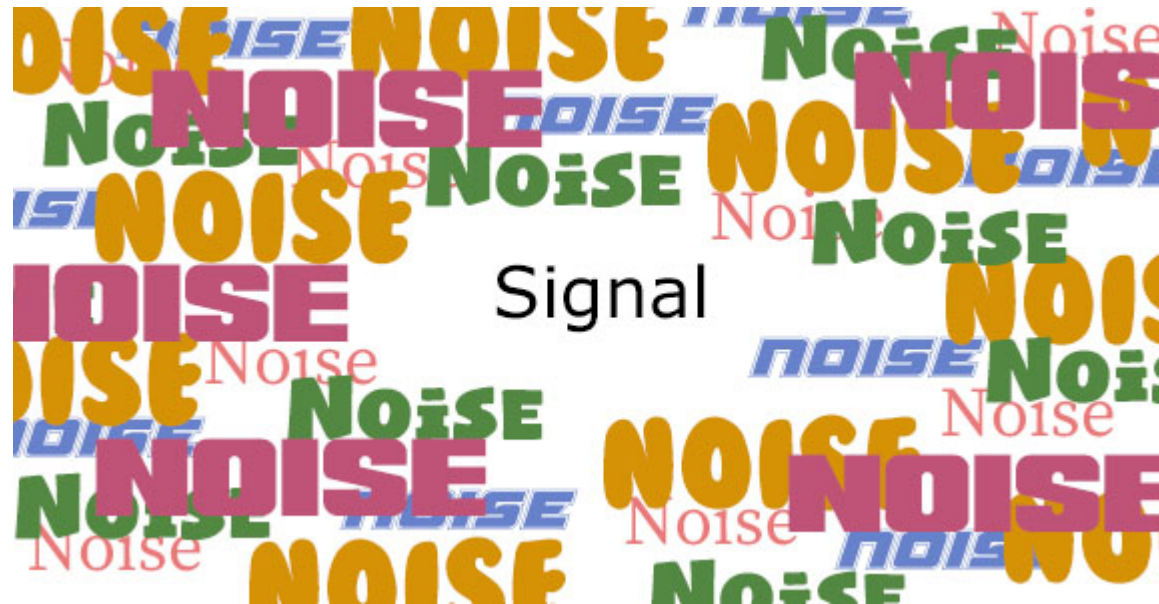
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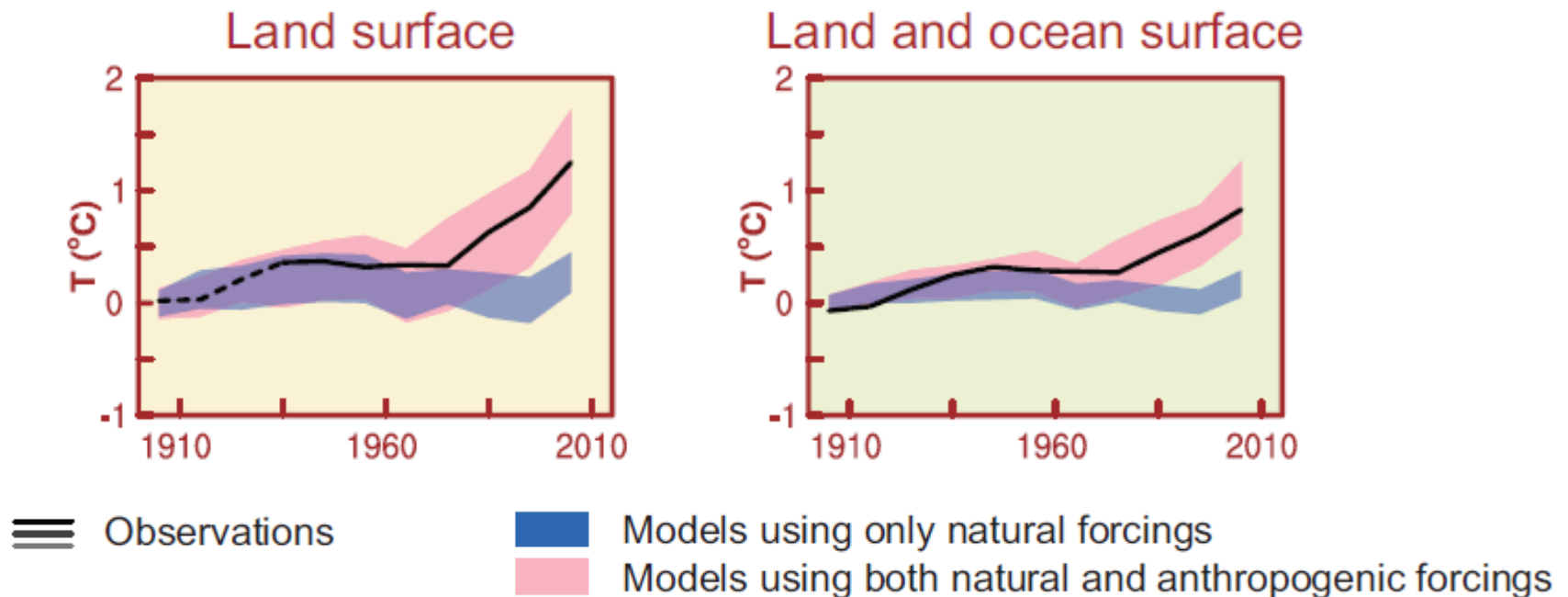
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Identifying an anthropogenic influence in the observational record is challenging



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Globally averaged surface temperature



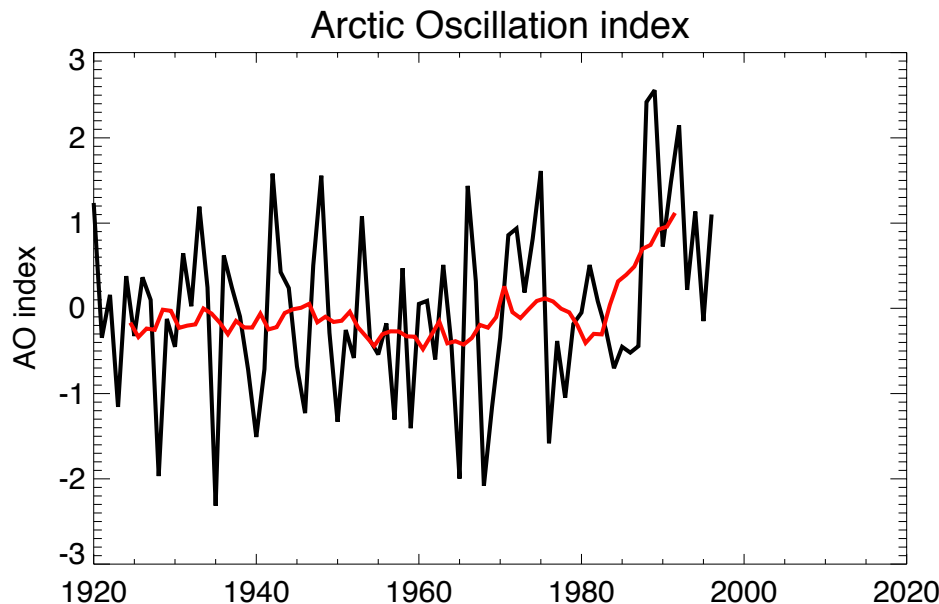
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Back in the 80's...



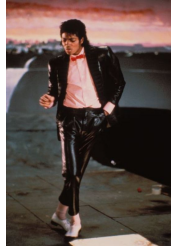
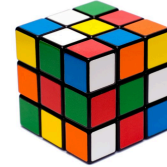
...there was an apparent trend in the Arctic Oscillation (AO) and the North Atlantic Oscillation (NAO)



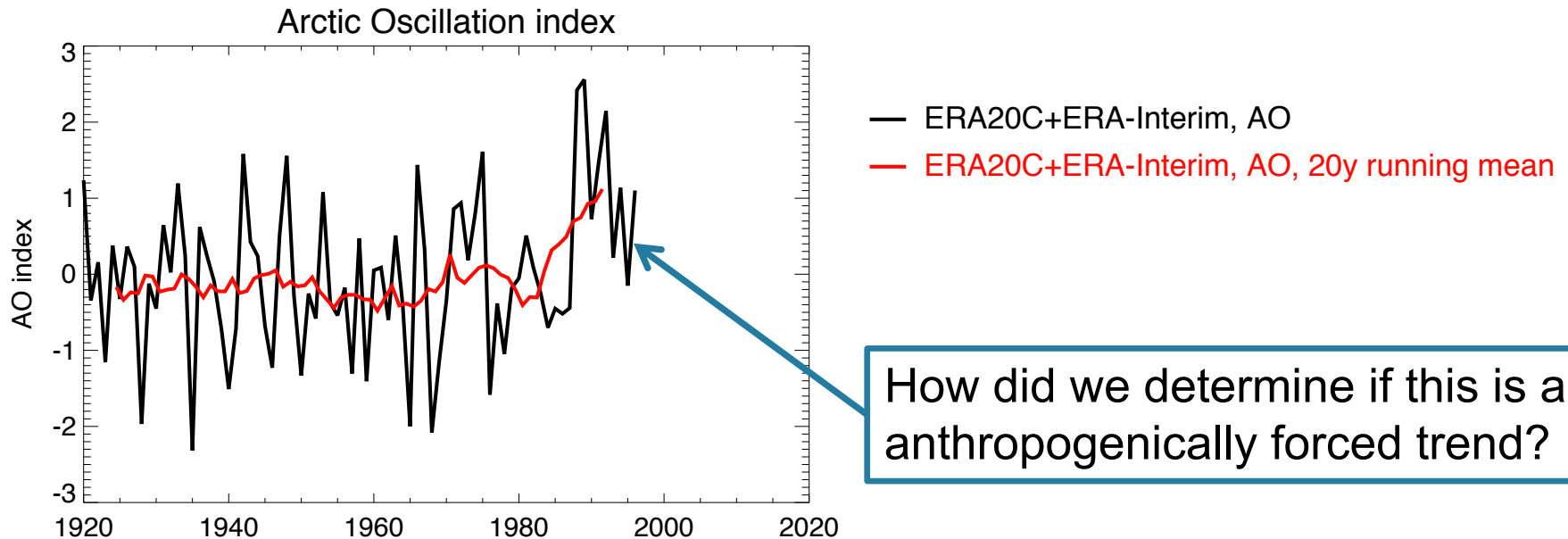
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Statistical Modelling

The Interpretation of Short Climate Records, with Comments on the North Atlantic and Southern Oscillations



Carl Wunsch

Program in Atmospheres, Oceans, and Climate, Department of Earth, Atmospheric, and Planetary Sciences, Massachusetts Institute of Technology, Cambridge, Massachusetts

The Timescale, Power Spectra, and Climate Noise Properties of Teleconnection Patterns

STEVEN B. FELDSTEIN

Earth System Science Center, The Pennsylvania State University, University Park, Pennsylvania

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Numerical Modelling

Shindell et al 1999, Fyfe et al 1999, Rodwell et al 1999, Hoerling et al 2001, Schneider et al 2003, Bracco et al 2004, Hurrell et al 2004, Selten et al 2004, Raible et al 2005, Deser and Phillips 2009, Scaife et al 2009

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letters to nature

Simulation of recent northern winter climate trends by greenhouse-gas forcing

Drew T. Shindell^{*†}, Ron L. Miller^{†‡}, Gavin A. Schmidt^{*†} & Lionel Pandolfo[§]

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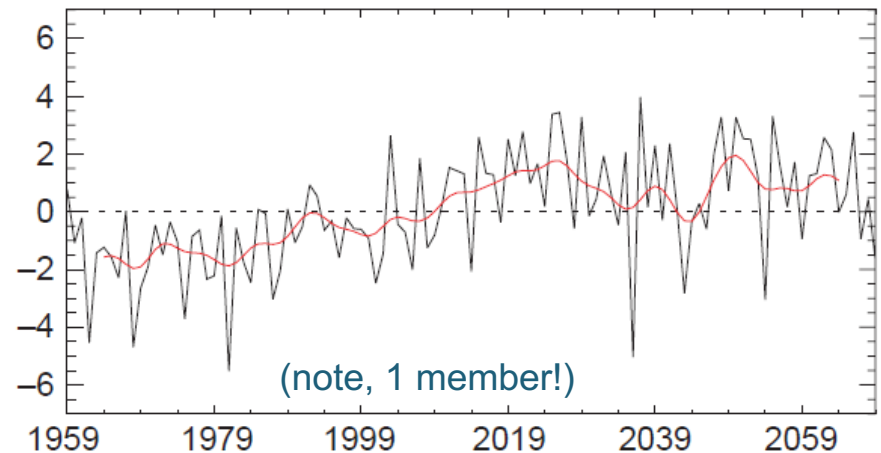
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Arctic oscillation, GISS model forced with GHG's
Well resolved stratosphere



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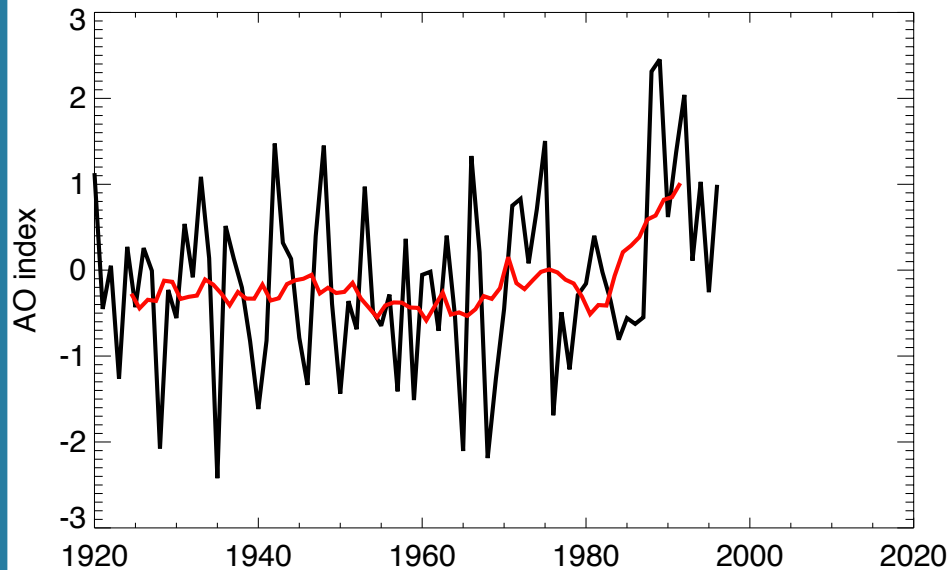
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Arctic Oscillation index

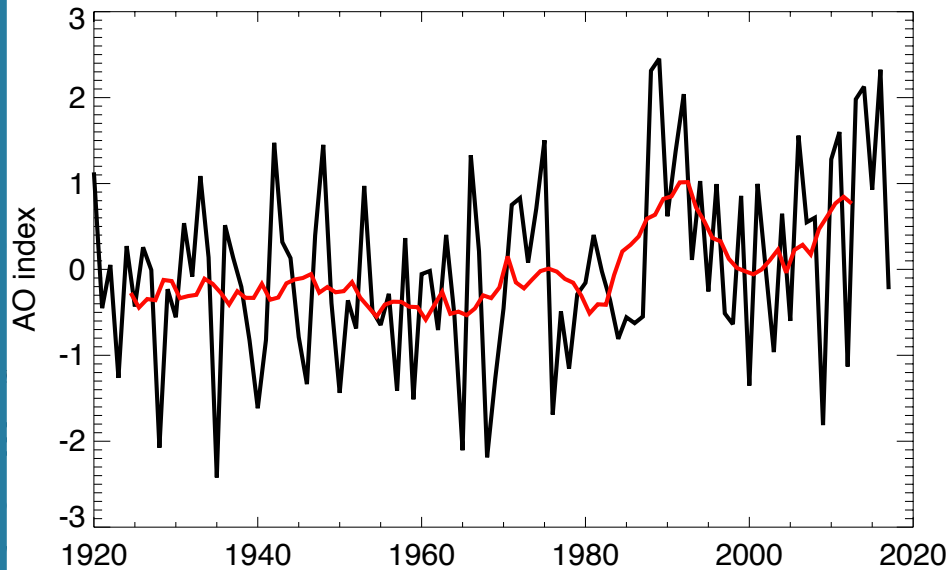


— ERA20C+ERA-Interim, AO
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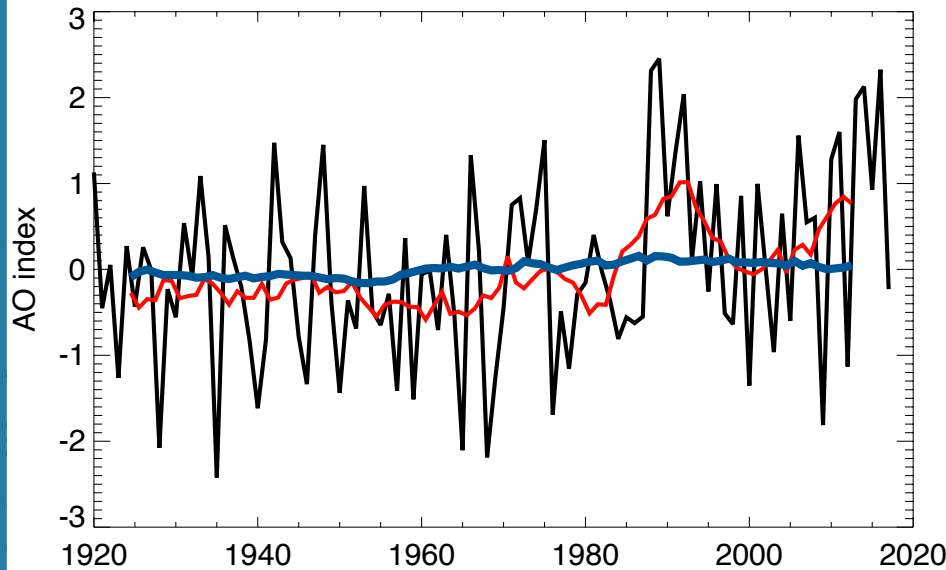


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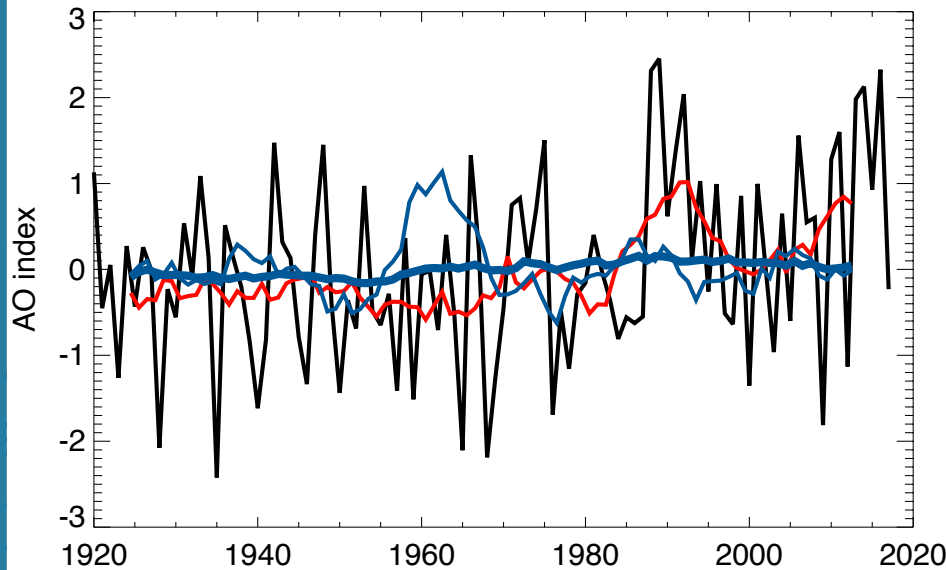


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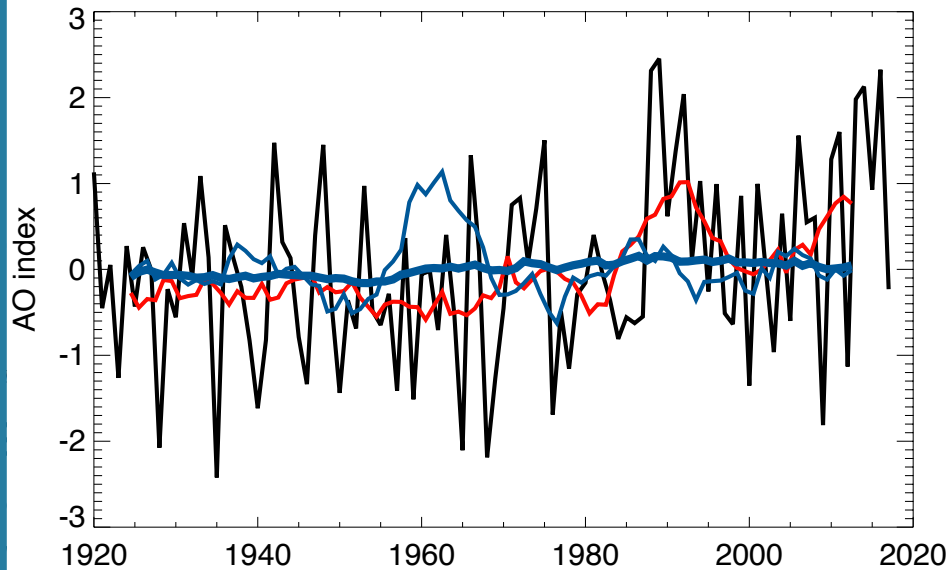


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“Before concluding that one is seeing evidence for trends, shifts in the

“..an increase in the AO index consistent with the recent observed

Positive trends in the Arctic Oscillation/Northern Annular Mode are expected to occur under GHG forcing (Gillett and Fyfe 2013, Barnes and Polvani 2013, IPCC AR5) but internal variability was likely an important contributor to the trends that were observed in the later part of the 20th century (e.g., Schneider et al 2003)

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Statistical Modelling

Limitation = Doesn't tell you what the actual anthropogenic contribution to change is.

Numerical Modelling

with a large enough ensemble

Limitation = You have to trust that the forced change and the internal variability are represented correctly in the model.

Discussion questions...

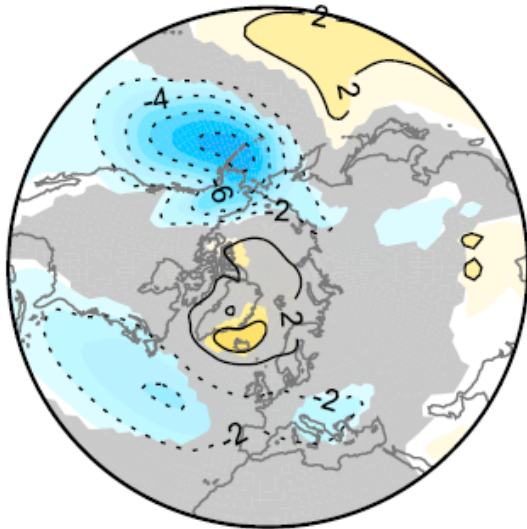
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Validating the teleconnection response to ENSO

SLP response to ENSO
El Nino – La Nina, 1920-2013



20CR

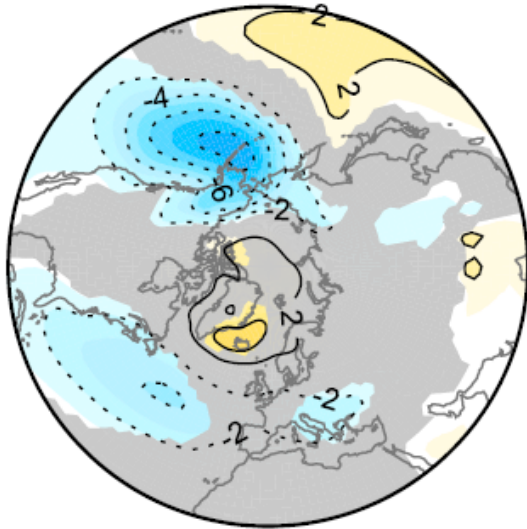
(observation based reanalysis)

Composite of 18 El Nino events
minus 14 La Nina events from the
observational record



Validating the teleconnection response to ENSO

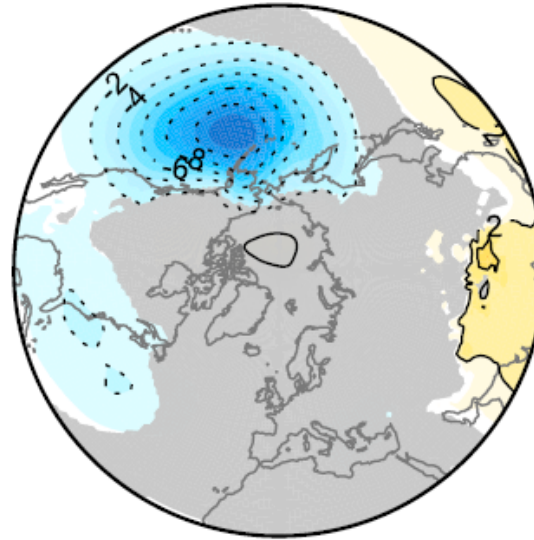
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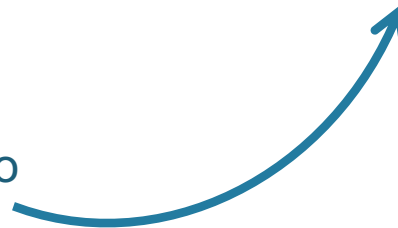
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Member A



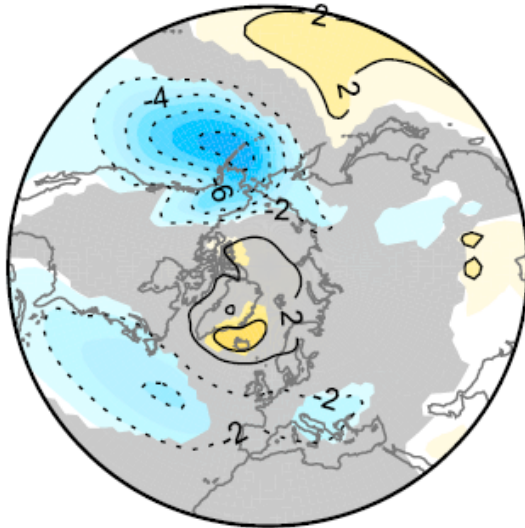
Model simulation with CESM1 where
the SSTs have been relaxed towards
obs in the tropical Pacific (pacemaker)

One model member, 18 El Nino
events – 14 La Nina events



Validating the teleconnection response to ENSO

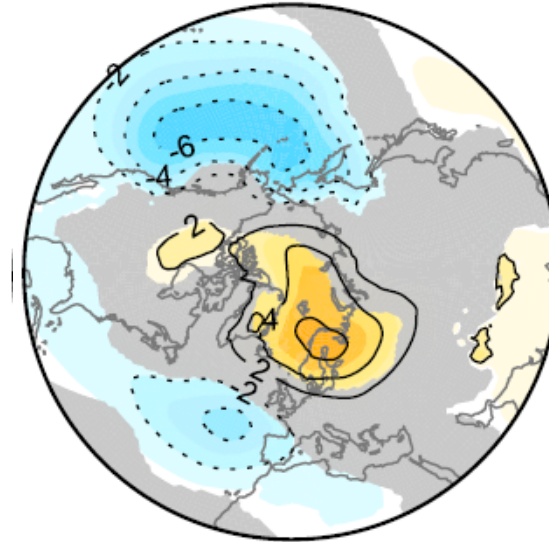
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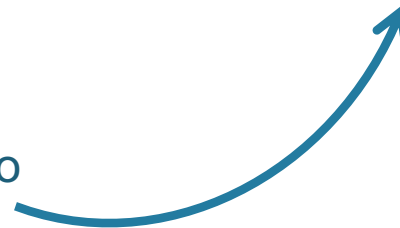
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Member B



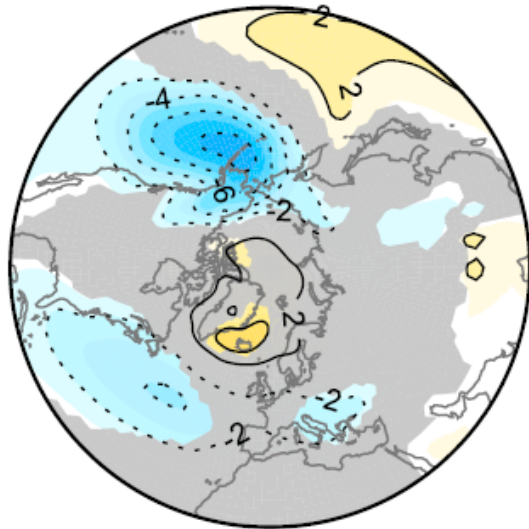
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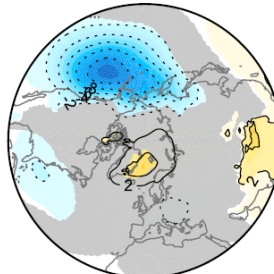
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El Nino – La Nina, 1920-2013

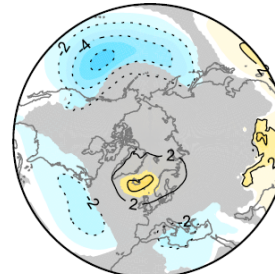


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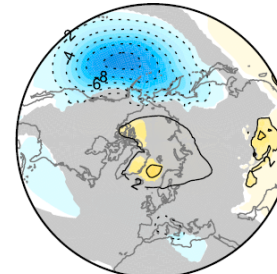
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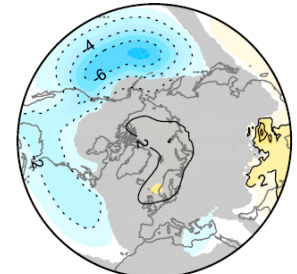
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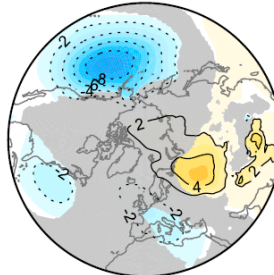
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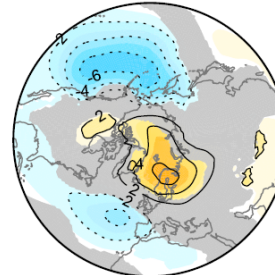
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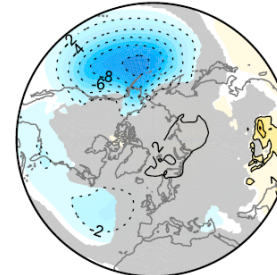
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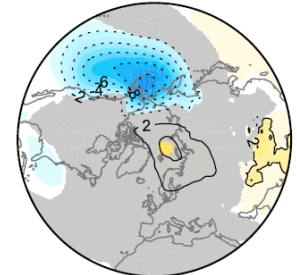
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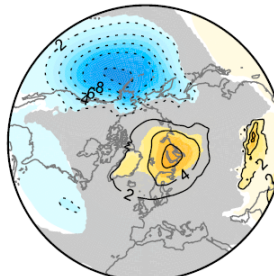
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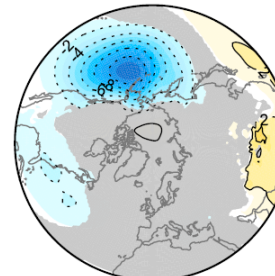
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#08



#09

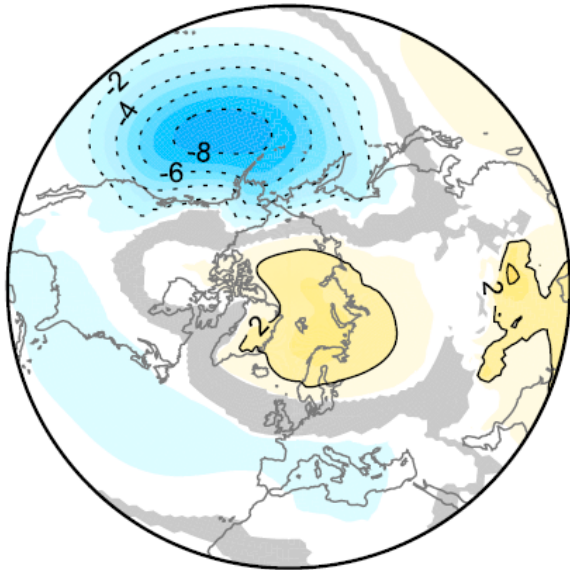


#10

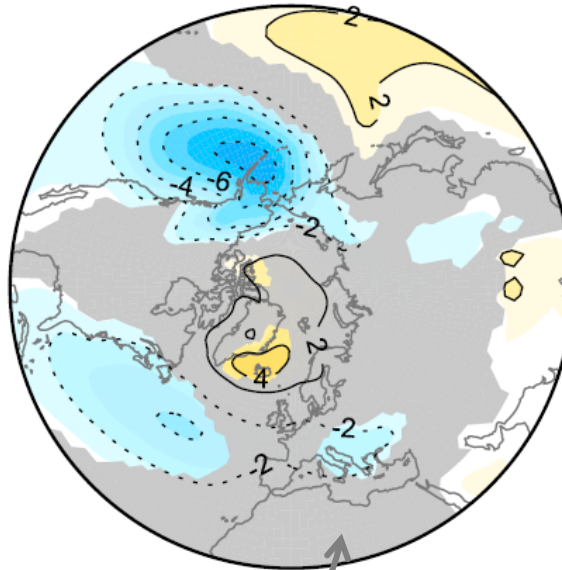
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SLP, El Nino – La Nina, 1920-2013 (18 El Nino's, 14 La Nina's)

CESM1 ensemble mean



20thC reanalysis

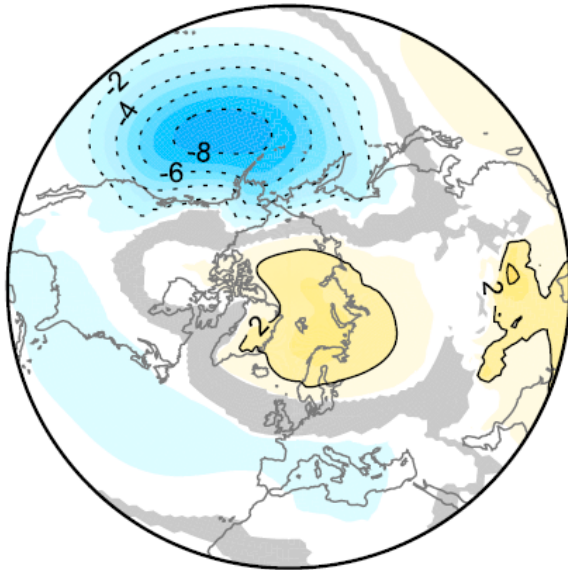


Gray = not significantly different from 0 at the 95% level by a one-sided t test

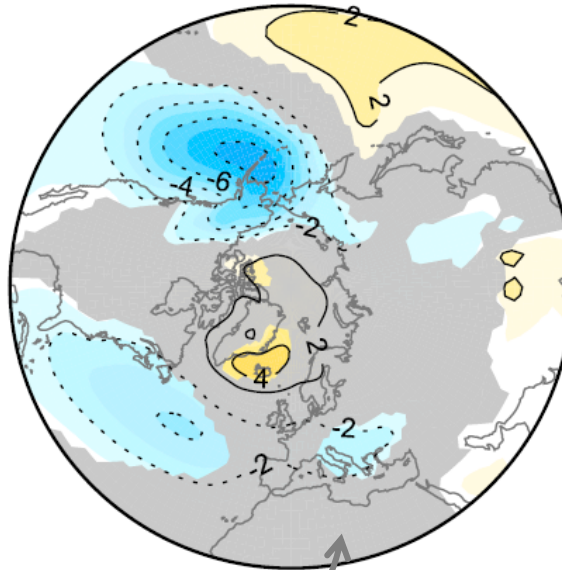
Validating the teleconnection response to ENSO

SLP, El Nino – La Nina, 1920-2013 (18 El Nino's, 14 La Nina's)

CESM1 ensemble mean



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How can we determine if they are different?

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Bootstrapping:

Randomly sample an equivalent number of El Nino and La Nina events to that in the observational record from our 10 members pooled together, many times.

Assess where does the real world sit within this bootstrapped distribution? Where are there indications of a bias in the model?

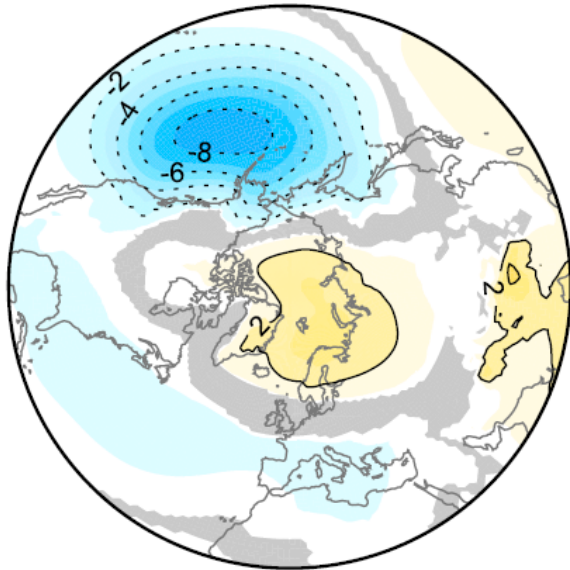
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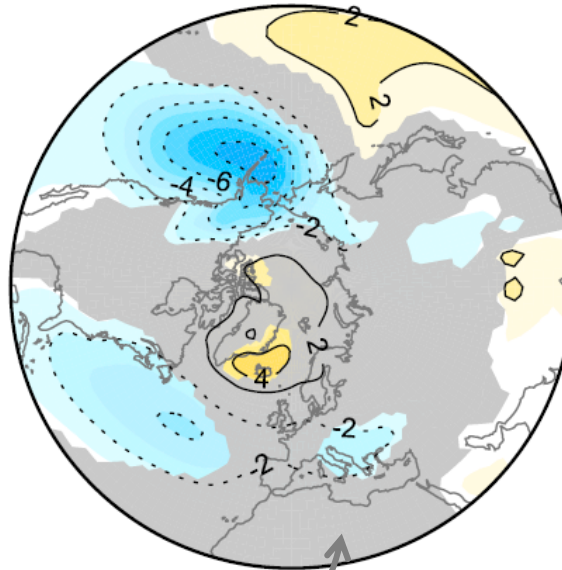
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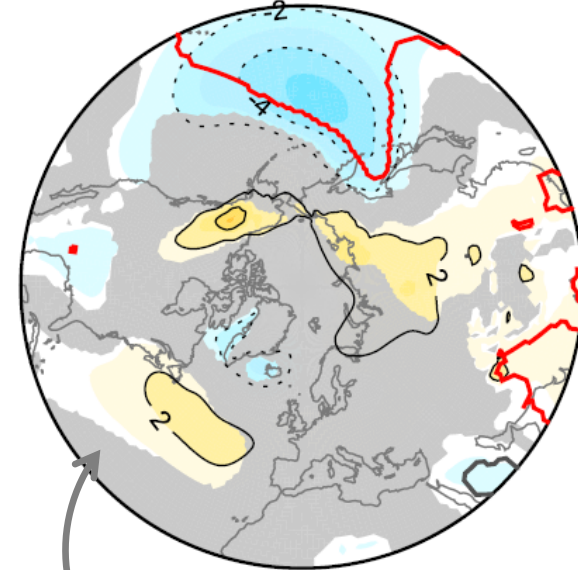
CESM1 ensemble mean



20thC reanalysis



CESM1 – 20thC reanalysis



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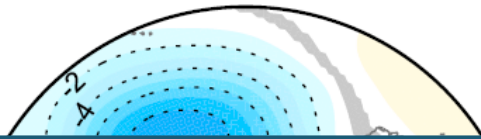
Gray = observations lie within the 5th-95th percentile range of 2000 bootstrapped differences between 18 El Nino's and 14 La Nina's, taken from the 10 CESM1 members pooled together

Where the reanalysis lies outside of the distribution of the 2000 bootstrapped ENSO composites.

Validating the teleconnection response to ENSO

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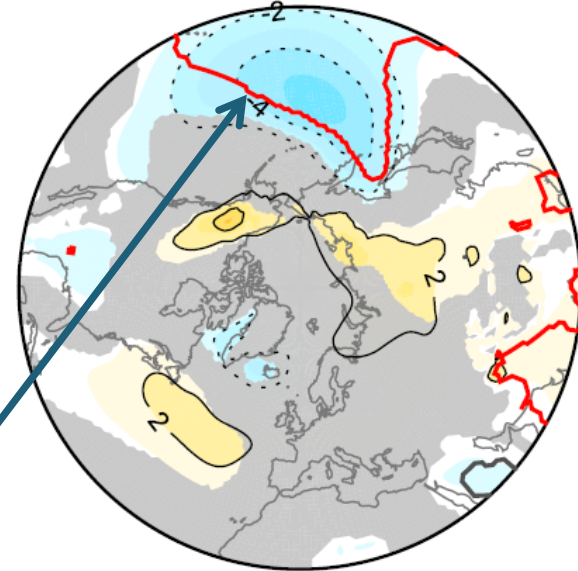
CESM1 ensemble mean



20thC reanalysis



CESM1 – 20thC reanalysis



Has to be accompanied by an assessment of the confidence that the modelled variability in composites is representative of the real world uncertainty too.

Can perform similar bootstrapping approaches on the observations, provided you have enough observational data.

Regions lie within the 5th-95th percentile range of 2000 bootstrapped differences between 18 El Nino's and 14 La Nina's, taken from the 10 CESM1 members pooled together

Where the reanalysis lies outside of the distribution of the 2000 bootstrapped ENSO composites.

Discussion questions...

- (1) In your subfield/specialty, what approaches are used to identify anthropogenic influences in the observational record? What are the main hurdles to doing this and how are they best overcome? In what aspects of the observed record is there confidence in an anthropogenic influence and its magnitude and in what aspects are there not?
- (2) How are model mean state, trends and/or variability typically validated in your particular subfield/specialty? Can this be improved upon with large ensembles and/or statistical methods applied to observations (i.e., an “observational LE”)? If so, how?
- (3) Within your subfield, what are the largest contributors to projection uncertainty (model structural, internal variability, forcing scenario) and what is the potential for narrowing them?

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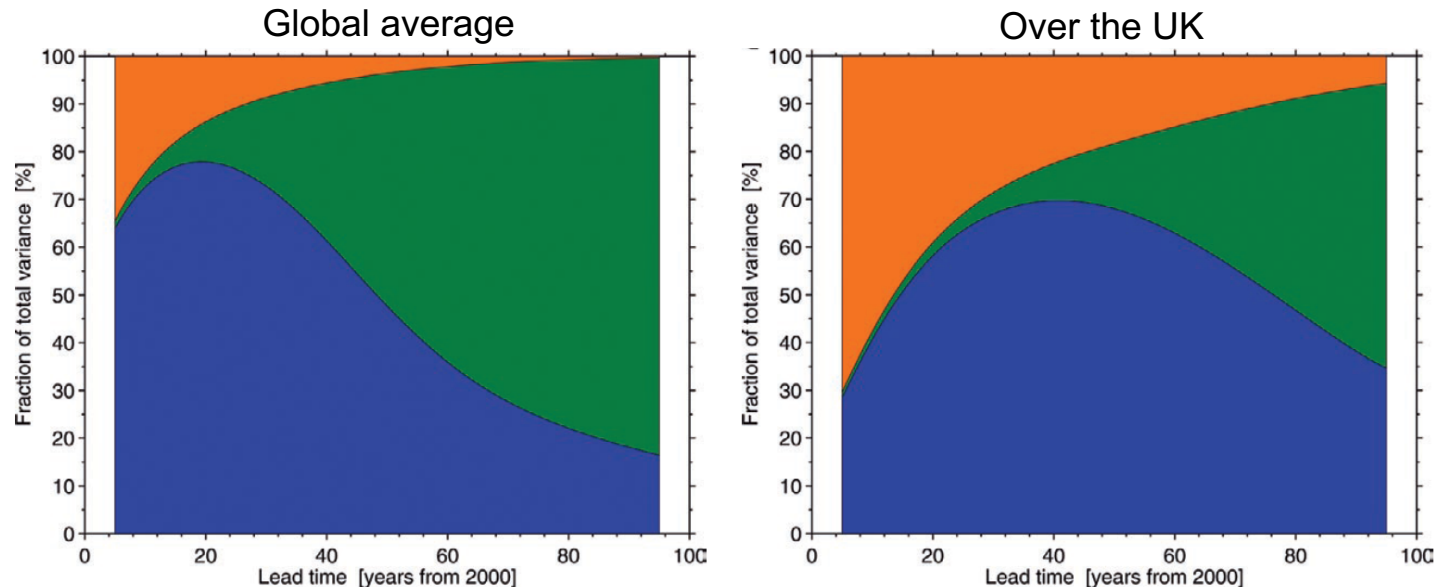
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Relative importance of different sources of uncertainty in decadal mean surface air temperature trends. Uses 15 models. (Hawkins and Sutton 2009)

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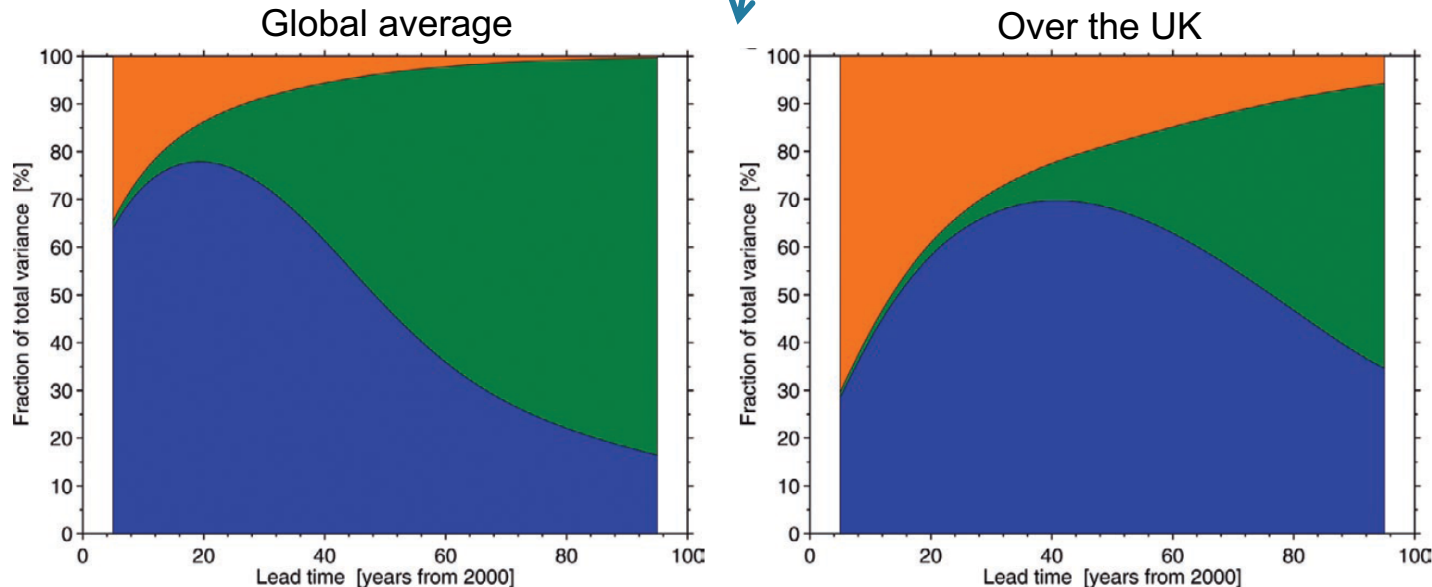
(c) **Scenario uncertainty** – uncertainty in the forcing scenario to evolve.

Had to make some assumptions...

Forced response determined by a 4th order polynomial fit to each realization

Internal variability doesn't change with time

Uses a multi-model mean estimate of internal variability



Relative importance of different sources of uncertainty in decadal mean surface air temperature trends. Uses 15 models. (Hawkins and Sutton 2009)

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Discussion Groups (both days, 3.45-5pm)

Group 1, Tower B penthouse: **Flavio Lehner**, **Tom Delworth**, Riley Brady, Amy Clement, Oscar Dimdore-Miles, Naomi Goldenson, Haruki Hirasawa, Kezhou Lu, Weiming Ma, Anna Merrifield, Gabriela Negrete Garcia, Nico Wienders, Colin Zarzycki

Group 2, Tower A room 315: **Clara Deser**, **James Randerson**, Tara Banerjee, Christopher Callahan, Neven Fuckar, Linnia Hawkins, Shihan Li, Gavin Madakumbura, Sebastian Milinski, Thierry Penduff, Hillary Scannell, Samantha Stevenson, Filippos Tagklis, Benjamin Toms

Group 3, Inner Damon Room: **Karen McKinnon**, **Pedro Dinezio**, Charles Curry, Luke Gloege, Forrest Hoffman, Xingying Huang, Alexandra Jahn, Robb Jnglin Wills, Kristen Krumhardt, Yochanan Kushnir, Valerio Lembo, Xiao-Wei Quan, Daniel Swain, Danielle Touma

Group 4, Fleishmann Building: **Nikki Lovenduski**, **Arlene Fiore**, Libby Barnes, Stefaan Conradie, Andrea Dittus, Ambarish Karmalkar, Martin Leduc, Joanna Lester, Abdul Malik, Wonsun Park, Bryn Ronalds, Deepti Singh, Detlef Stammer, Gan Zhang

Group 5, Outer Damon room: **Isla Simpson**, **Claude Frankignoul**, Sebastian Eastham, Melissa Gervais, Patrick Kinney, Giovanni Liguori, Justin Mankin, Holly Olivarez, Lorenzo Polvani, Mercedes Poso Buil, Sean Ridge, Daniel Schmidt, Haiyan Teng, Honghai Zhang, Sally Zhang

Group 6, Chapman room: **Mingfang Ting**, **John Fyfe**, Amy Braverman, Hui Ding, Mark England, Aixue Hu, Jeremy Klavans, Sydney Kramer, Elizabeth Maroon, Clio Michel, Eleanor Middlemas, Matt Newman, Daniel Vecellio, Lei Wang

Group 7, Directors conference room (215): **Daniel Horton**, **Keith Rodgers**, Dillon Amaya, Seung Hun Baek, Alejandro Flores, Fernando Garcia Menendez, Jingyuan Li, Nicola Maher, Precious Mongwe, Lawrence Mudryk, Annika Reintges, Alan Robock, Karen Smith

Group 8, Library: **Shoshiro Minobe**, **Jen Kay**, Raul Wood, Tamas Bodai, Kathleen Holman, Antonios Mamalakis, Ben Santer, Sarah Schlunegger, Kevin Schwarzwald, Abby Stevens, Jozef Syktus, Yohei Takano, Kasia Tokarska, Jiacan Yuan

END

Statistical Modelling

The Interpretation of Short Climate Records, with Comments on the North Atlantic and Southern Oscillations



Carl Wunsch
Program in Atmospheres, Oceans, and Climate, Department of Earth, Atmospheric, and Planetary Sciences, Massachusetts Institute of Technology, Cambridge, Massachusetts

The Timescale, Power Spectra, and Climate Noise Properties of Teleconnection Patterns

STEVEN B. FELDSTEIN

Earth System Science Center, The Pennsylvania State University, University Park, Pennsylvania

Statistically model the noise of the system according to the properties you can observe.

“Before concluding that one is seeing evidence for trends, shifts in the means, or changes in oscillation periods, one must rule out the purely random fluctuations expected from stationary time series.” – Wunsch 1999

Numerical Modelling

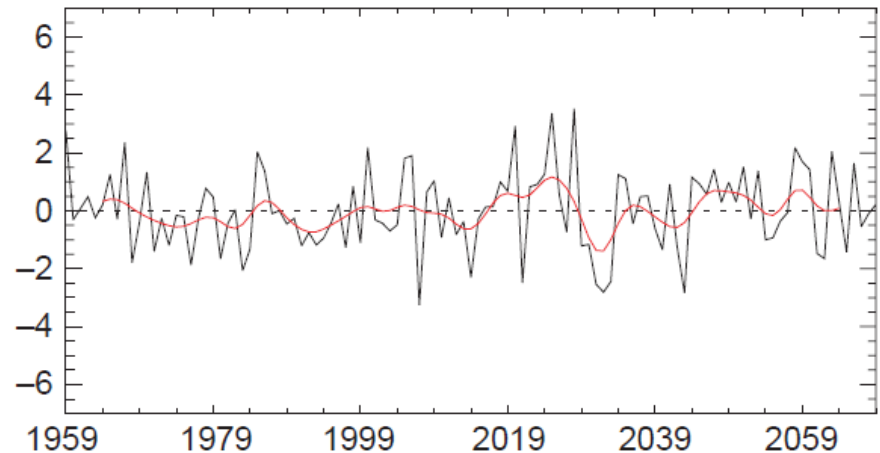
letters to nature

Simulation of recent northern winter climate trends by greenhouse-gas forcing

Drew T. Shindell^{*†}, Ron L. Miller^{†‡}, Gavin A. Schmidt^{*†} & Lionel Pandolfo[§]

Assessing whether a numerical model forced with rising GHG's reproduces the observed trend.

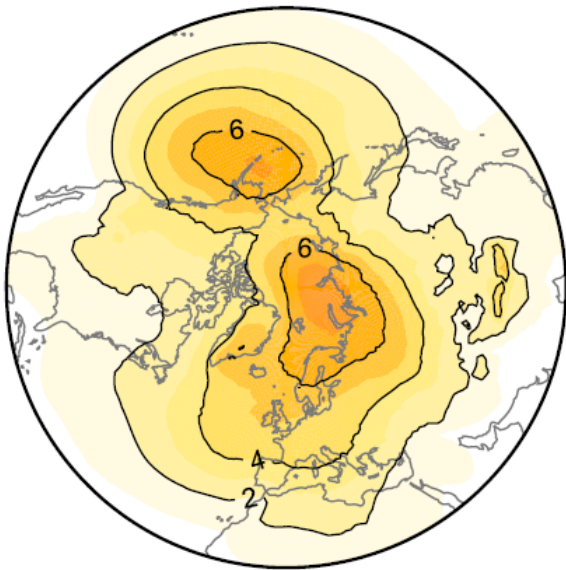
Arctic oscillation, GISS model forced with GHG's
Poorly resolved stratosphere



Validating the teleconnection response to ENSO

5th-95th percentile range of 2000 bootstrapped samples of 18 El Nino events – 14 La Nina events

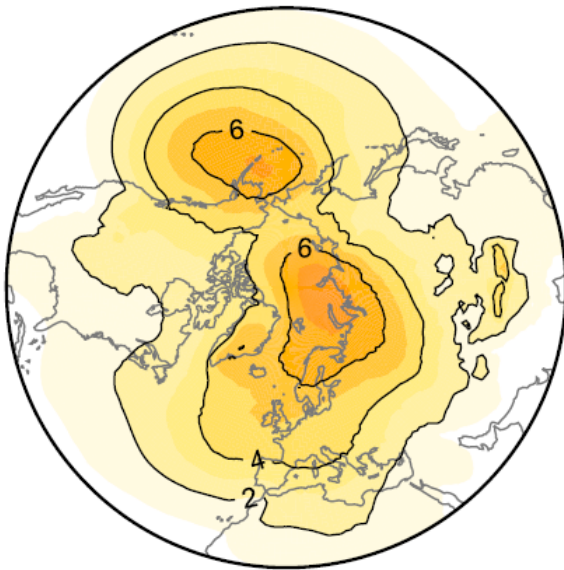
Bootstrapped samples
taken from the 10 CESM
members pooled together



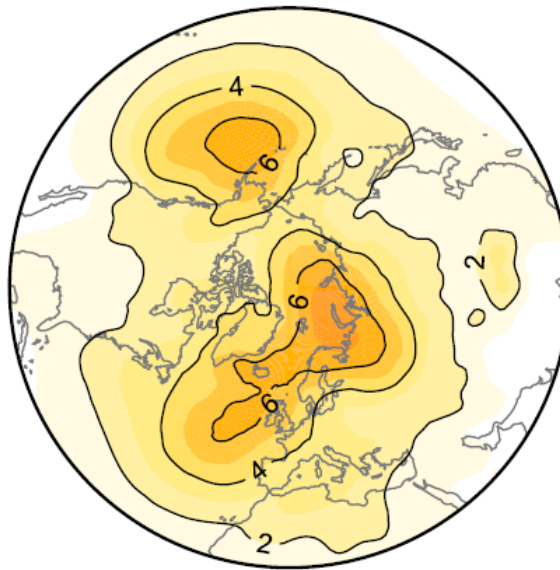
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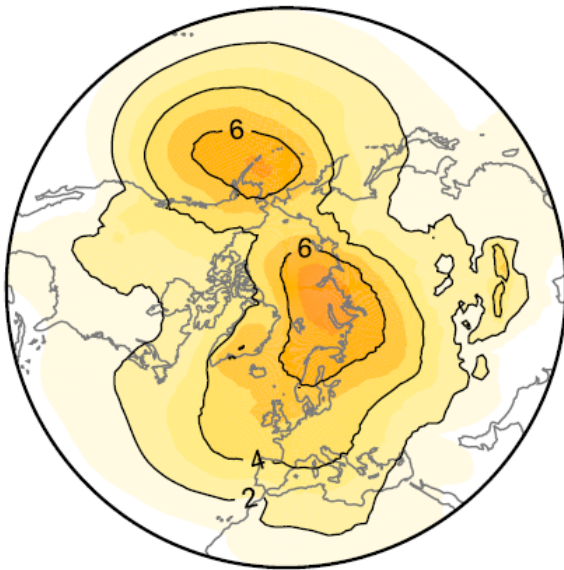
Bootstrapped samples
taken from reanalysis



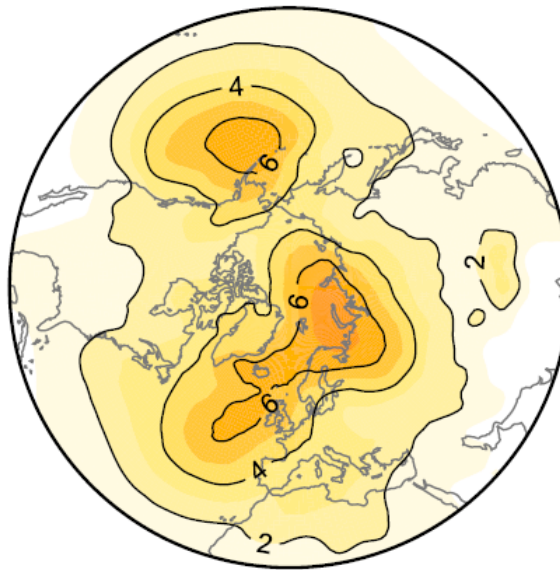
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Gray shading = where the observed range lies within the distribution of ranges obtained when generating the bootstrapped samples from each CESM1 member individually.

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